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ARMED SERVICES VOCATIONAL APTITUDE BATTERY (ASVAB): PREDICTING MILITARY CRITERIA FROM GENERAL AND SPECIFIC ABILITIES

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This report describes the effectiveness of observed measures of general and specific abilities for the prediction of training success. Scores on the Armed Services Vocational Aptitude Battery (ASVAB) were used to estimate the general and specific components of abilities for recruits in 125 military occupations across the four U.S. Armed Services. The results of this study replicated and extended the results of earlier investigations using Principal Components analysis of observed ASVAB scores. These studies indicated that psychometric general ability 'g' is usually the best predictor of training success as measured by final technical school grade and Skill Qualification Test scores for the sample of military occupations used in this study. However, measures of specific ability resulted in significant increments to validity for 118 of the 125 military occupations examined. For this sample of military jobs, some situational specificity was found; thus, continued use of measures of specific abilities appears warranted.

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SUMMARY

The purpose of this effort was to determine the contribution of measures of general and specific abilities to prediction of training success and Skill Qualification Test (SQT) scores for military recruits in the four Armed Services. Validity data for the Armed Services Vocational Aptitude Battery (ASVAB) for over 347,000 recruits were obtained for 808 occupational specialties for which criterion data were available. These data were examined to select military training courses that met a priori statistical power requirements.

Review of the literature indicated that three broad methods are typically used to estimate the **g** saturation in cognitive measures: hierarchical factor analysis, unrotated principal factor analysis, and unrotated principal components analysis. The decision to use unrotated principal components analysis was based on the simplicity of the method, the number of investigator judgements and decisions, and the uniformity of results. Principal components (PC) analysis was used with stepwise multiple regression to determine the contribution of specific and general abilities to prediction. General and specific abilities were estimated using the first unrotated principal component to estimate **g**; and s_2, $s_3 \ldots s_{10}$ specific abilities were estimated using the second through the tenth unrotated principal components from the intercorrelation matrix of ASVAB subtests used in the nationwide administration of the ASVAB in 1980.

Final military technical school grades for the Marine Corps, Navy and Air Force recruits, and SQT scores for Army recruits, in occupations meeting power requirements for the study were regressed in stepwise fashion onto the recruits' PC-weighted ASVAB subtest scores. The order of entry of the PC estimates of **g** and s_2, $s_3 \ldots s_{10}$ into the prediction equations for each job was noted.

The results of this study replicated and extended the results of earlier investigations using principal components analysis of observed ASVAB scores that indicated that psychometric **g** is consistently the best predictor of training success as measured by final technical school grade and Skill Qualification Test scores for the sample of 125 military occupations used in this study. However, measures of specific ability added significant increments to validity for 118 of the 125 military occupations examined. For this sample of military jobs, some situational specificity was found; thus, continued use of measures of specific abilities appears warranted.

PREFACE

This research and development work was conducted under Contract No. F41689-87-D-0012/5012, Task 11, Armed Services Vocational Aptitude Battery (ASVAB): Predicting Military Criteria from General and Specific Abilities. The authors wish to acknowledge the support provided in the form of validity data from the Navy Personnel Research and Development Center, the Center for Naval Analysis, and the Army Research Institute for the Behavioral and Social Sciences. Special recognition goes to Dr. Pamla Palmer, Mr. Carl Haywood, and Ms. Lynn Trent for their assistance and considerable skill in reducing over 325,000 cases of validity data for analysis. Dr. Ben Fairbank and Dr. Don Burdick provided valuable guidance and necessary tables for the power analysis.

TABLE OF CONTENTS

LIST OF TABLES

ARMED SERVICES VOCATIONAL APTITUDE BATTERY (ASVAB): PREDICTING MILITARY CRITERIA FROM GENERAL AND SPECIFIC ABILITIES

I. INTRODUCTION

This report describes the effectiveness of measures of specific and general abilities for prediction of training success and Skill Qualification Test (SQT) scores of military recruits. Armed Services Vocational Aptitude Battery (ASVAB) scores were used to estimate general and specific components of ability for military recruits in 125 military occupations in the four U.S. Armed Services. The usefulness of these components of specific and general ability for predicting military criteria was estimated using stepwise multiple regression.

The ASVAB has been used for years by the Armed Services to select and classify personnel into a large array of military occupations. ASVAB subtests, like subtests of most multiple-aptitude batteries, are positively intercorrelated. Thus, the ASVAB subtests measure some general underlying cognitive attribute, as well as the specific abilities they were designed to measure.

Inclusion of measures of specific abilities in the ASVAB represents a school of thought that specific or unique abilities are of primary importance for predicting training success or other criteria for a variety of occupations. Thorndike (1985) noted that this view about the usefulness of measures of specific abilities has not always prevailed. The recent personnel testing literature has shown a shift from the importance of specific abilities to an advocacy of the importance of General Cognitive Ability (g) for prediction. This shift represents a return to an earlier view about the nature of human ability.

Spearman (1904, 1927) first referred to g as a common factor that emerged from factor analysis of many sets of ability measures. Spearman also maintained that intelligence was composed of two factors: one general factor, g, which was common to all tests of cognitive ability, and a specific factor s that remained unique to any given measure of specific ability. Later, as factor analytic techniques were widely applied to different types of measures, group factors were discovered in which different types of tests (e.g., psychomotor and spatial perception tests) tended to load together on different group factors.

Some cognitive measures tended to cluster with other measures of the same group factor; this led Spearman to hypothesize that all measures in the cognitive domain have different, non-zero amounts of **g**.

During the 1930's and 1940's, the literature concerning measurement of human abilities was marked by the emergence of the school of thought which maintained that human ability was composed of multiple, specific abilities as opposed to a single, unitary construct like Spearman's **g**. Thurstone (1938), applying the centroid method of factor analysis, identified primary mental abilities which he claimed were independent of Spearman's **g**. Thurstone's work sparked a continuing debate in the literature even though Thurstone (Thurstone & Thurstone, 1941) admitted that a general factor was necessary to explain the intercorrelations among his primary factors.

Vernon (1950) and Moursy (1952) proposed a hierarchical theory of human abilities that featured major group factors, as well as minor factors of human abilities. At the time, this model of human abilities failed to gain much empirical support and consequently did not exert much influence.

In the following two decades, three major reviews of the literature on the predictive utility of tests of cognitive ability provided evidence of the overarching importance of **g** for prediction of educational and occupational success criteria (Ghiselli, 1966 & 1973; McNemar, 1964). McNemar's analysis led him to conclude that differential validity could not be found in a representative multiple-aptitude battery for prediction of educational criteria. In his landmark summary of aptitude test validation research, Ghiselli (1966) reached conclusions which were opposed to those of McNemar (1964). However, Ghiselli failed to take into account sampling error in the hundreds of validity coefficients used in his meta-analysis. The Ghiselli (1966, 1973) studies were often used to support the doctrine of situational specificity, the contention that prediction of occupational success criteria is contingent on unique patterns of specific abilities. It was not until Schmidt and Hunter (1977) reanalyzed Ghiselli's (1966) work -- correcting his data for sampling error, as well as other sources of error variance in the validity coefficients -- that debate over the efficacy of **g** versus **s** was brought back into the literature. The role of **g** and **s** in prediction prompted a special edition of the Journal of Vocational Behavior (Gottfredson, 1986).

Mayr (1982) and Weinberg (1988) have described the issue in terms of a continuing dialogue between "lumpers" and "splitters." The splitters' school of thought defines human ability in terms of multiple, specific abilities. According to this view, human cognitive ability can be defined in terms of separate, distinct abilities. This position contrasts with that of the lumpers, who maintain that human cognitive ability is a single capability underlying all measures of specific cognitive abilities.

It is probably a mistake to pit one school of thought against the other, in that both viewpoints have merit. Also, the one ability versus multiple abilities distinction may be an oversimplification. Hunter, Crosson, and Friedman (1985) claimed there are two levels of factors which coexist in test batteries: aptitudes which explain "fine-grain" clustering and general second-order abilities which account for the correlations among aptitudes. Measures of specific cognitive abilities will correlate highest with other specific measures of the same type and will be positively correlated with all other cognitive measures. The magnitude of this correlation depends on the g saturation of the specific measure involved. Thus, the practical issue is the relative contribution of measures of specific abilities versus general cognitive ability in prediction.

The Role of g and s in Situational Specificity

Since before World War II, the splitters have held a dominant position in arguing for the practical utility of measures of specific cognitive ability in military selection and classification. This position is congruent with the notion of situational specificity which maintains that jobs require unique patterns of abilities for successful accomplishment of job-related tasks. Therefore, according to proponents of this view, to predict job success one has to find that combination of specific abilities which relates to job proficiency and performance.

The work of Schmidt and Hunter (1977) has lessened the dominance of the splitters in the specific versus general abilities debate. Schmidt and Hunter's (1977) research spawned a large body of literature on the generalizability of the validity of a large number of specific ability measures across a large number of jobs. The situational specificity of employment tests for prediction of job performance or proficiency has been assumed by many psychologists over the years. Schmidt, Hunter, and Pearlman (1981) used meta-analytic techniques to show that most of the apparent variability in test validity is due to statistical artifacts such as sampling error, unreliability of measurement, unreliability of criterion measures, and restriction in the range of abilities in specific samples. A number of other researchers (Guzzo, Jette, & Katzell 1985; Hyde, 1981; Linn, Harnisch & Dunbar, 1981; Schmidt, Gast-Rosenberg, & Hunter, 1980; Schmidt, Hunter, & Caplan, 1981; Steele & Ovalle, 1981) have also applied meta-analytic techniques to large numbers of validity studies across scores of different jobs and found little variance in validity coefficients that could not be explained by these four statistical sources of variance (Schmidt, Hunter, Pearlman, & Shane, 1979). Little, if any, variance was explained by factors specific to a given type of criterion.

Thorndike (1985) reanalyzed three sets of data on the predictive validity of three commonly used multiple-aptitude batteries in an effort to understand the validity generalization of measures of cognitive ability. He examined validity data for the following three multiple-aptitude batteries for job and training success in civilian and military jobs: the Differential Aptitude Test (DAT), the General Aptitude Test Battery (GATB), and the Army Classification Battery (ACB). These batteries contain between eight and ten subtests that measure both **g** and **s**. However, Thorndike's (1985) reanalysis shows that a common factor among each of the three batteries explained between 60% and 120% more systematic criterion variance than did cross-validated, regression-weighted composites. Thorndike argued that such results indicate the widespread validity of **g** as a predictor of job proficiency and training success. Furthermore, he argued that the **g** saturation of tests of specific abilities is the basis for the apparent generalizability of cognitive tests across job situations. Thorndike estimated that only between 10% and 15% additional criterion variance beyond that predicted by **g** is likely to be explained with regression-weighted composites of specific abilities.

The work of Hunter and others (Hunter, 1986; Jensen, 1986; Thorndike, 1986) indicates that any specific test of cognitive ability or any multiple-aptitude battery of cognitive tests will have greater criterion-related validity to the extent that the measures correlate with **g**. The majority of the research in this area has used meta-analytic techniques to obtain averaged estimates of the validity of measures across job families in order to obtain sufficient sample sizes with sufficient statistical power. Hunter, Crosson, and Friedman (1985) maintained that use of measures of specific aptitudes or abilities provided little increment in validity over the substantial validity of **g**.

Recent research by Jones (1988) supports the view of Hunter et al. (1985). Jones used the ASVAB standardization sample consisting of a nationwide sample of American Youth (ages 18 to 23) administered the ASVAB in 1980 (U.S. Department of Defense (DoD), 1982) to analyze a population intercorrelation matrix using Principal Components (PC) analyses. This collection of 9,173 American youth was a stratified probability sample weighted to represent a youth population of over 25 million Americans. Jones used these population estimates for the intercorrelations of the ASVAB subtests and estimated the **g** saturation of the subtests, using PC analysis. The first principal component accounted for about 64% of the common variance among subtests in the population correlation matrix and was conventionally defined as g.

Jones' (1988) results indicate that the subtests' g-loading is significantly related to the averaged criterion-related validity of subtests, within broad aptitude areas. Her research supported the hypothesis that g is a potent predictor of entry-level Air Force training success with a rank-order correlation of .72 between the weighted average validity of 37 Air Force jobs and the g saturation of the ASVAB subtests. Jones' results, however, provided little information about the contribution of specific abilities, as measured in the ASVAB, for predicting training success.

Ree and Earles (1990a), extending the work of Jones (1988), used the complete set of 10 PCs from the ASVAB normative sample intercorrelation matrix to estimate and compare the predictive utility of **g** (estimated by the first unrotated PC) with that of the set of specific abilities in the ASVAB (estimated by the remaining nine PCs). The predictive utility of **g** as estimated by the unrotated first PC was substantial across 89 Air Force jobs, with an average $R^2 = .58$, corrected for range restriction. The total sample for the Ree and Earles (1990a) study consisted of 78,049 Air Force recruits; within individual Air Force technical school courses, samples ranged from 274 to 3,930 recruits. The increment to predictive utility added by the estimates of specific abilities was an average squared multiple R of .02.

The apparent pervasiveness of **g** in cognitive ability tests has important practical ramifications. Hunter and Schmidt (1982) estimated that tests of cognitive ability, when used in an appropriate utility model, could save the Government several billion dollars. The usefulness of tests of cognitive ability for selection and classification systems has an acknowledged history. What is unclear is the usefulness of measures of specific ability in adding predictive utility beyond that provided by the **g** component.

Methods of Estimating g

The implications to be drawn from the **g** versus **s** debate have been obscured by the use of at least three analytic methods: (a) hierarchical factor analysis, (b) unrotated principal factors analysis, and (c) unrotated principal components (PC) analysis. These methods all have merit, but differing results and conclusions may emanate from their use. They seem to differ in the number and type of decisions required of the researcher. Two researchers making slightly different, but equally justified, decisions could arrive at very different conclusions about the underlying structure(s) of a set of cognitive measures. For this reason, these three methods are examined below in terms of the nature and number of decisions required and in the uniformity of results obtained (Ree & Earles, 1990b).

Hierarchical Factor Analysis

The use of hierarchical factor analysis to examine the structure and relationship of aptitudes dates back to work done by Vernon (1950) and Moursy (1952). A more recent example of the use of the hierarchical factor analytic approach is the work of Hunter, Crosson, and Friedman (1985).

Support for the hierarchical model comes from factor analytic theory and studies which employ oblique rotation after factor extraction through either principal components, principal factors, or other extraction methods. The first-order factor intercorrelation matrix is then re-factored and the resultant matrix of intercorrelations of the second-order factors are factored. This process continues until only one or two factors remain. The first factor serves as the estimate of **g**.

In using the hierarchical factor analytic approach, decisions have to be made about the number of factors to extract at each level of the analysis. Other decisions about the communalities and the degree of factor intercorrelation to accept could lead to differing estimates of **g**. Hierarchical approaches require the most judgements and decisions on the part of the analyst, and tend to provide the least uniform results of the three methods.

Unrotated Principal Factors

The principal or common factors method analyzes the reduced intercorrelation matrix and requires decisions on what to use as a measure of the communality in the diagonal (Muliak, 1972). There are at least four common methods for estimating the communality: squared multiple correlations, iterative squared multiple correlations, highest correlation of a variable in the matrix, and the reliabilities of the variables. The solutions are not rotated to provide an estimate of **g** in the first principal factor. Uniformity of results can vary as a function of the method used to estimate the communalities.

Principal Components (PC) Analysis

The PC method requires fewer decisions and provides a completely determined result. Thus, it also provides the most uniform results. The PC approach permits stable estimates of the proportion of variance in the ASVAB attributable to g and specific components of cognitive ability $s_1, s_2, \ldots s_n$, and avoids the problem of replicability of results associated with the choices and judgements involved with the other two methods of estimating **g**. Ree and Earles (1990b) compared all three methods and concluded that all three solutions are so highly related (the lowest correlation among solutions was .93) that the methods could be used interchangeably in practice. However, they argued that the PC method was preferred because it was the simplest method and provided the most uniform results. Research employing PC analysis has been used to investigate the relative contribution of general and specific abilities in predicting military criteria (Jones, 1988; Ree & Earles, 1990a, 1990b, 1990c).

Purpose of Present Research

The purpose of the present research is to explore the relative contributions of general and specific abilities (as measured by the ASVAB) for the prediction of military training success and other criteria. In doing so, the investigators examine the relative predictive utility of estimates of g and s using principal components analysis to determine whether the doctrine of situational specificity applies to a large sample of military jobs. This PC analysis uses military validity data from the ASVAB. All analyses were conducted within each military occupation, selected on the basis of a priori statistical power levels. Unrotated PC analysis was chosen as the method to estimate g and s because it requires the fewest number of decisions and provides the most uniform results.

II. METHOD

Subjects

Subjects for this study were military recruits in the four U.S. Armed Services. Validity data on recruits were provided by four Service-specific military personnel research laboratories across 808 military occupations. Sample sizes by Service were as follows: Army, N = 166,011; Navy, N = 47,318; Air Force, N = 117,872; and Marine Corps, N = 16,497. Descriptive statistics for gender, ethnicity, and test form for the total data set of 347,698 military recruits are provided in Table 1 by Service. Ethnic group membership data were not available from the Navy.

Table 1. Demographics of Services' Validity Data

Group	N	Proportion	Total
		Army	
Male	148,149	89.2%	
Female	17,862	10.8%	166,011
White	112,630	67.8%	
Black	45,622	27.5%	
Hispanic	7,731	4.7%	
Other or Unknown	28	0.0%	166,011
Test Form			
8	20,265	12.2%	
9	62,463	37.6%	
10	83,283	50.2%	166,011
		Navy	
Male	41,936	88.6%	
Female	5,382	11.4%	47,318
White	No Information Available		
Black	No Information Available		
Hispanic	No Information Available		
Other or Unknown	No Information Available		
Test Form			
8	4,015	8.5%	
9	9,114	19.4%	
10	12,096	25.7%	
11	6,964	14.8%	
12	6,509	13.9%	
13	6,065	12.9%	
14	2,215	4.7%	46,978
		Air Force	
Male	97,243	82.5%	
Female	20,629	17.5%	117,872
White	94,404	80.0%	
Black	16,709	14.2%	
Hispanic	3,274	2.8%	
Other or Unknown	3,485	3.0%	117,872
Test Form			
11	40,966	34.8%	
12	38,594	32.7%	
13	38,312	32.5%	117,872
		Marine Corps	
Male	15,309	92.8%	
Female	1,188	7.2%	16,497
White	13,178	79.9%	
Black	2,742	16.6%	
Hispanic[a]			
Other or Unknown	577	3.5%	16,497
Test Form			
8	5,814	35.3%	
9	5,631	34.2%	
10	5,021	30.5%	16,497

[a]None specified.

Measures

Predictors

The ASVAB is used by the U.S. Military to select and classify applicants into a large array of military occupations. The ASVAB is a multiple-aptitude battery composed of 10 subtests with content, test length, and subtest times as shown in Table 2.

Table 2. Content of ASVAB Forms 8 through 17

Subtest	Description	Number of items	Test time (mins)
General Science (GS)	Knowledge of the physical and biological sciences	25	11
Arithmetic Reasoning (AR)	Word problems emphasizing mathematical reasoning rather than mathematical knowledge	30	36
Word Knowledge (WK)	Understanding the meaning of words (i.e. vocabulary)	35	11
Paragraph Comprehension (PC)	Presentation of short paragraphs followed by one or more multiple-choice items	15	13
Numerical Operations (NO)	A speeded test of four arithmetic operations (i.e. addition, subtraction, multiplication and division)	50	3
Coding Speed (CS)	A speeded test of matching six-digit numbers	84	7
Auto & Shop Information (AS)	Knowledge of auto mechanics, shop practices and tool functions in verbal and pictorial items	25	11
Mathematics Knowledge (MK)	Knowledge of algebra, geometry, and fractions	25	24
Mechanical Comprehension (MC)	Understanding mechanical principles such as gears, levers, pulleys and hydraulics in verbal and pictorial items	25	19
Electronics Information (EI)	Knowledge of electronics and radio principles in verbal and pictorial items	20	9
Total		334	144

Predictors were the 10 principal components of the 10 ASVAB subtests' standard scores. The PC weights were taken from Ree and Earles (1990a) and are shown in Table 3, along with eigenvalues and the percent of variance accounted for by each of the principal components. These components are based on the intercorrelations of ASVAB subtest scores obtained from a stratified probability sample of American youth who took the ASVAB in 1980 (DoD, 1982). Principal components scores were computed by weighting subtest standard scores by the component weights. Each subject had 10 principal component scores.

Table 3. Principal Component Weights Used to Generate Individual Component Scores

	Principal Component				
Subtest	1	2	3	4	5
GS	.13808	-.11244	-.21982	-.29416	.19523
AR	.13715	.03854	-.39912	.54694	-.02066
WK	.13736	.06649	-.21381	-.64261	-.08976
PC	.12778	.16656	-.31273	-.71570	-.02359
NO	.11291	.38342	.42663	.23843	-1.36760
CS	.09956	.44464	.75816	.03679	1.11560
AS	.10878	-.43374	.60474	-.00918	-.34001
MK	.12965	.12086	-.61486	.64452	.20353
MC	.12448	-.30623	.21087	.39938	.36281
EI	.12857	-.29635	.14351	-.13640	-.00001
Eigenvalue	6.39381	1.28974	.52171	.50951	.28978
Percent Variance	63.9	12.9	5.2	5.1	2.9
	6	7	8	9	10
GS	-.88893	-1.05107	.56764	.46367	-1.25618
AR	.26159	.58641	.25640	-1.51740	-1.06178
WK	-.20343	-.35471	.19392	-1.22910	1.53259
PC	1.10958	.48914	-.18581	.83254	-.55741
NO	-.11449	-.39672	-.29306	.20266	-.11527
CS	-.14894	.21734	.13184	-.06193	-.04099
AS	.22086	.62982	1.28389	.27471	.26269
MK	-.26607	.28551	.29615	1.16925	1.09690
MC	.89768	-1.19071	-.72807	-.02996	.28081
EI	-.78167	.90823	-1.43032	.09391	-.06884
Eigenvalue	.27006	.21101	.20511	.16081	.14846
Percent Variance	2.7	2.1	2.1	1.6	1.5

Criteria

The criterion measure was final technical school grade for those military occupations meeting statistical power requirements for the Navy, Air Force, and Marine Corps. The Army supplied Skill Qualification Test (SQT) scores as a criterion measure. Although SQT scores are not job performance measures, in contrast to final technical school grade they do reflect proficiency acquired on-the-job. This is due to the fact that SQT scores are obtained after Army recruits leave initial, entry-level training and have been in their initial job assignment for some time (Wagner, Dirmeyer, Means, & Davidson, 1982). Use of a different Army criterion measure should not have an appreciably negative impact on the comparability of analyses across services, because the Army SQT should be predicted in about the same manner as final course grades (Hunter, 1983a, 1983b).

Analytic Procedure

Power Analysis - Sample Size

Power requirements were established so that samples for each military job would be of sufficient size to detect an increment in multiple R's (for the regression of the criterion on the PC predictors) of .1 at alpha = .05 with a power of at least .50. A conservative expected validity coefficient of .20 was used. Power analysis showed that samples of approximately 550 individuals or greater would meet the requirements of this study. One hundred twenty-five military occupations which met or exceeded these size requirements were selected from the provided data sets.

Principal Components and Regression Analysis

The criterion was regressed on the 10 principal components in a stepwise fashion. The order of entry of the principal components in a stepwise multiple regression is an indication of the importance of the component for prediction. The order of entry of the different components can be compared across jobs to give an aggregate picture of principal component predictive utility. All data used in this effort were restricted in range of abilities and, therefore, the R^2 values are underestimates.

III. RESULTS AND DISCUSSION

The descriptive statistics of the 10 ASVAB subtests' raw scores for the 125 military occupations meeting the statistical power requirements are contained in Appendix A. Full job titles of the 125 military jobs identified as meeting the power requirements are listed in Appendix A. Also provided in Appendix A are the sample size, the criterion means, and standard deviations. Descriptive statistics of the ASVAB subtests and subtest intercorrelations are available from the authors upon request.

Multiple R's are presented in Table 4. The R_g is the correlation associated with the first PC, the estimate of g. The R_{g+s} is the multiple R associated with the first PC, plus any components that resulted in statistically significant increments to the R_g for that job. R_{diff} is the difference between the two (R_g - R_{g+s}), or the estimate of the contribution to prediction of the PCs taken as estimates of specific abilities.

Table 4. Average Multiple R's, Standard Deviations, and Ranges for Principal Component Composites by Service

Multiple R	Mean	SD	Range High	Range Low
		Army		
R_g	.364	.080	.553	.135
R_{g+s}	.409	.080	.610	.184
R_{diff}	.046	.035	.167	.006
		Navy		
R_g	.184	.067	.317	.040
R_{g+s}	.233	.071	.344	.077
R_{diff}	.049	.030	.141	.016
		Air Force		
R_g	.230	.073	.455	.076
R_{g+s}	.269	.071	.477	.113
R_{diff}	.039	.020	.030	.008
		Marine Corps		
R_g	.305	.095	.411	.194
R_{g+s}	.354	.070	.450	.274
R_{diff}	.048	.028	.080	.009

Differences in predictive utility among the Services are reflected in the higher predictive utility of the first PC or **g** for the Army and Marine Corps than for the Air Force and Navy. Again, this is most likely attributable to differential range restriction. Examination of the raw score descriptive statistics and the coefficients of variation in Appendix A shows substantial differences among the Services and jobs.

Higher predictive utility of R_g, as well as the greater range and mean of R_{diff} for the Army, may also lie in the different nature of the Army criterion. SQT scores are qualitatively different from the final course grades provided by the other Services. The SQT scores represent a combination of a job knowledge test and a hands-on performance test and are obtained after graduation from technical training school in the recruits' first term

Differential range restriction remains the most viable explanation of the higher Army multiple R's. However, data are used in this form by all of the Services' personnel selection and classification systems. Thus, it is informative to examine validities and predictive utilities within Service and within a given military job without corrections for range restriction.

The stepwise multiple regression of the 10 PC composites was accomplished within each of the 125 military jobs. Tables 5 through 8 show the results of the stepwise regression of criteria on the 10 PCs, with the order of entry of the principal component for prediction of the criteria. Only those PC composites that resulted in a statistically significant increment in the multiple R at the .05 level are listed. R_g is almost universally the best predictor of the criterion measures across Services, consistent with the findings of Ree and Earles (1990a) for a sample of Air Force jobs.

The coefficient of multiple determination (squared multiple R) should be used to compare the magnitude of the correlations. For the Army, the average R_g^2 was .13; for the Navy, R^2_g = .02; for the Air Force, R^2_g = .05; and for the Marine Corps, R^2_g = .09. The proportion of common variance attributable to the specific abilities PCs, is indicated here by the average R^2_{diff} for the four Services. For the Army, R^2_{diff} = .035; for the Navy, R^2_{diff} = .020; for the Air Force, R^2_{diff} = .020; and for the Marine Corps, R^2_{diff} = .032. There are differences in the contributions of specific and general abilities of about 1% to 1.5% across the Services. This is again consistent with the results of Ree and Earles (1990a) for Air Force jobs.

Table 5. Regression Analyses of Final School Grades And SQTs on Principal Components for Army Specialties

		Principal Component Order of Entry											
MOS[a]	N	1	2	3	4	5	6	7	8	R_g	R_{g+s}	R_{diff}	SEE[b]
05H	637	1	2	3	7					.291	.346	.055	7.893
11B	17805	1	2	3	8	6				.441	.449	.008	10.418
11C	3968	1	8	2						.410	.417	.007	9.632
11H	2732	1	2	8						.404	.417	.013	9.751
12B	4517	1	2	4	5					.389	.403	.014	9.720
12C	1052	1	2	3	4	10				.372	.421	.049	9.025
13B	10678	1	2	4	3					.361	.376	.015	11.233
13F	1899	1	4	3	8	2				.448	.473	.025	9.705
15D	997	1	8							.295	.315	.020	12.544
16P	962	1	2	7	9	4				.290	.377	.087	8.441
16R	738	1	2							.409	.463	.054	6.934
16S	1273	1	4	2	8					.316	.364	.048	9.228
19D	3319	1	2	8	4	3				.431	.454	.023	9.540

Table 5. (Continued)

MOS[a]	N	Principal Component Order of Entry 1	2	3	4	5	6	7	8	R_g	R_{g+s}	R_{diff}	SEE[b]
19E	4064	1	2	8	6	4				.432	.447	.015	8.135
19K	1497	1	2							.441	.447	.006	9.278
31C	3683	1	2							.469	.476	.007	9.135
31K	3129	1	2	4	5	7	10			.382	.428	.046	8.607
31M	2834	1	2							.399	.422	.023	9.565
31V	1049	1	2	9						.340	.372	.032	9.155
32D	552	1								.248	.299	.051	8.867
36C	1840	1	2	4	3					.280	.354	.074	10.477
43E	613	1								.191	.217	.026	13.183
51B	550	1	2	8	4					.449	.488	.039	9.527
52D	2044	1	2	6						.343	.360	.017	8.310
55B	1139	1	3							.274	.295	.021	10.965
57H	639	1								.262	.283	.021	12.459

Table 5. (Continued)

MOS[a]	N	Principal Component Order of Entry 1	2	3	4	5	6	7	8	R_g	R_{g+s}	R_{diff}	SEE[b]
62B	1095	1	2	3	4	6				.491	.606	.115	10.104
62E	978	1	2	5	4					.417	.457	.040	10.800
62J	577	1	2							.416	.444	.028	10.950
63B	6948	1	2	3	4	7	8	6	9	.409	.484	.075	8.810
63D	590	2	1	7	6	3				.312[c]	.479	.167	7.755
63H	1452	1	2	3	7	4	8	9	6	.553	.610	.057	9.335
63N	984	1	2	6	3					.292	.422	.130	7.661
63S	622	1	2	7	3					.323	.393	.070	8.715
63T	1369	2	1	8	3	4	5	6		.286[c]	.426	.140	7.397
63W	1367	1	2	3	8	4				.494	.606	.112	8.130
64C	7493	1	2	6	3	9	8			.369	.395	.026	8.148
67N	951	1	2							.257	.345	.088	8.723
67V	714	1	2	3	8					.388	.453	.065	7.474

Table 5. (Continued)

MOS[a]	N	Principal Component Order of Entry								R_g	R_{g+s}	R_{diff}	SEE[b]
		1	2	3	4	5	6	7	8				
67Y	564	1	2							.327	.400	.073	8.482
71L	6069	1	2	3	5	9	7	6		.382	.432	.050	12.451
72E	2560	1	3	4	8					.391	.405	.014	9.760
72G	959	1	3	4						.457	.478	.021	8.546
73C	761	1	2	8	4	3	7			.287	.350	.063	9.636
75B	996	1	2	10	7	3				.446	.487	.041	12.060
75C	694	1	4	2	3					.428	.483	.055	11.551
75D	1342	1	2	3	4					.394	.432	.038	11.886
76C	2891	1	4	3	7	5	8			.316	.360	.044	8.462
76P	1609	1	4	2	7	3	10			.268	.327	.059	12.748
76V	2176	1	4							.296	.306	.100	9.233
76W	2049	1	2	4	10	7				.454	.485	.031	10.233
76Y	5337	1	2	7	3	8	10	5		.342	.351	.009	10.696

Table 5. (Concluded)

MOS[a]	N	Principal Component Order of Entry								R_g	R_{g+s}	R_{diff}	SEE[b]
		1	2	3	4	5	6	7	8				
82C	758	1	4	7	3					.460	.514	.054	10.503
91E	552	1	2							.342	.372	.030	8.681
92B	667	1	4							.135	.184	.049	12.898
94B	6039	1	2	4	8	7	9			.342	.364	.022	9.045
95B	9066	1	3	6	2	9	4	8	10	.341	.359	.018	7.359
98C	616	1	8	3	5					.301	.343	.042	10.571

[a]MOS defined in Appendix A.
[b]SEE = Standard Error of Estimate.
[c]Because the first PC did not enter the regression first, R_g is not, in this instance, a measure of the predictive utility of g, but instead the specific ability measured by the specific PC.

Table 6. Regression Analyses of Final School Grades and SQTs on Principal Components for Air Force Specialties

AFSC[a]	N	Principal Component Order of Entry 1	2	3	4	5	6	7	8	R_g	R_{g+s}	R_{diff}	SEE[b]
25130	639	1	4	6						.340	.382	.042	29.675
27230	1269	1	6	3	4					.455	.477	.022	34.133
27630C	681	1	7							.285	.297	.012	12.275
30434	1513	1	4	5	7	9	3			.269	.346	.077	31.308
32430	770	1	7	4	3					.320	.360	.040	29.903
32531	688	1	4	7						.268	.343	.075	32.388
32830	645	1	4	7						.274	.329	.055	30.472
32831	646	1	6	7						.344	.376	.032	33.224
32833	675	1	2	4						.212	.249	.032	40.994
41131A	552	1	7							.310	.343	.033	14.495
42330	995	1	6	9	4					.261	.307	.046	28.284
42735	796	1	2	4						.160	.230	.070	17.413
45234	3851	1	2	8	9	4				.307	.319	.017	13.166

Table 6. (Continued)

AFSC[a]	N	Principal Component Order of Entry 1	2	3	4	5	6	7	8	R_g	R_{g+s}	R_{diff}	SEE[b]
45430A	2003	1	3	6						.232	.249	.017	24.943
45431	2355	1	7	2	4					.226	.257	.031	26.486
45433	627	1	6							.155	.196	.041	23.414
45434	781	1	2	9	10	4				.145	.225	.080	24.766
45450A	610	7								.085[c]	.129	.044	28.238
45730	2712	1	2	7						.276	.306	.030	13.390
45732	2146	1	2							.274	.290	.016	14.450
45732C	645	1	2							.118	.187	.069	38.098
46130	2311	1	8	4						.209	.228	.011	12.269
46230E	769	1	3	4						.203	.249	.046	15.780
46230F	855	1	7							.234	.263	.029	16.028
46230K	596	1	9							.246	.284	.038	13.321
46330	592	1								.234	.282	.048	25.647

Table 6. (Continued)

		Principal Component Order of Entry											
AFSC[a]	N	1	2	3	4	5	6	7	8	R_g	R_{g+s}	R_{diff}	SEE[b]
49131	2204	1	3	2	6					.263	.281	.018	13.591
49231	603	1	4	3						.244	.303	.059	19.220
55131	578	1								.233	.261	.028	10.921
57130	2082	1								.177	.186	.009	12.269
60531	1075	1	4							.223	.251	.028	13.308
62330	831	1	6	10						.153	.224	.071	13.158
63130	1692	1								.076	.113	.037	14.702
64530	3515	1	2	3	7					.210	.262	.052	9.938
67232	742	1	3							.232	.259	.027	18.674
70230	3922	1	2	4	5	3				.175	.226	.051	13.743
73230	1730	1	2							.233	.269	.036	22.620
81130	8830	1	9	4	3	6				.203	.211	.008	18.738
81132	4301	1	2							.224	.233	.009	23.158

<u>Table 6</u>. (Concluded)

		Principal Component Order of Entry											
AFSC[a]	N	1	2	3	4	5	6	7	8	R_g	R_{g+s}	R_{diff}	SEE[b]
81132A	572	1								.167	.200	.033	18.189
90230	2378	1	3	2						.146	.179	.033	21.579
90630	945	1	2	10						.174	.240	.066	15.390
92430	558	1	5	3	4	8				.336	.401	.065	34.101
98130	821	1	6							.194	.232	.038	23.232

[a]AFSCs defined in Appendix A.
[b]SEE = Standard Error of Estimation
[c]Because the first PC did not enter the regression first, R_g is <u>not</u>, in this instance, a measure of the predictive utility of g, but instead the specific ability measured by the specific PC.

Table 7. Regression Analyses of Final School Grades and SQTs on Principal Components for Navy Specialties

RATINGS[a]	N	Principal Component Order of Entry								R_g	R_{g+s}	R_{diff}	SEE[b]	Pwr[c]
		1	2	3	4	5	6	7	8					
6001	3134	1	4	2	6	8	9			.300	.344	.044	26.705	.863
6005	2388	1	4	2						.148	.164	.016	30.624	.198
6015	1910	1	2	3	6					.244	.265	.021	15.057	.249
601E	692	1	2	3	4	10				.156	.268	.112	10.416	.925
603V	3260	1	2	4						.126	.153	.027	13.284	.468
604E	2122	1	10							.152	.176	.024	11.504	.302
6068	1189	1	3	4	2	7				.159	.300	.141	23.566	1.000
6070	1464	1	2	8						.152	.205	.043	9.525	.518
607W	1652	1	7	4	2					.242	.264	.022	7.088	.241
611E	3013	1	4	2	10					.230	.297	.067	6.647	.990
611T	1519	8	1	3						.120[c]	.180	.060	17.869	.770
6125	8200	1	4	10	7	6				.125	.153	.028	20.695	.826
6167	1108	d								.040	.077	.037	19.348	.339

Table 7. (Concluded)

RATINGS[a]	N	Principal Component Order of Entry 1	2	3	4	5	6	7	8	R_g	R_{g+s}	R_{diff}	SEE[b]	Pwr[c]
6172	977	1								.133	.177	.044	10.446	.402
6278	986	1	6							.317	.341	.023	37.718	.196
6301	1222	1	4	3						.154	.218	.064	37.053	.746
6302	965	1	2							.184	.220	.036	20.283	.310
6472	627	1	4	8						.239	.308	.069	30.807	.577
6477	709	1	10							.139	.193	.054	7.879	.427
6515	2365	1	4	10	5					.216	.264	.048	30.049	.795
6537	908	1	4	5	2	6				.283	.334	.051	32.655	.510
6540	2076	1	4	9	3					.182	.223	.041	29.734	.615

[a]RATINGS defined in Appendix A.

[b]SEE = Standard Error of Estimate.

[c]Because the first PC did not enter the regression first, R_g is <u>not</u>, in this instance, a measure of the predictive utility of g, but instead the specific ability measured by the specific PC.

[d]No PC composite significant at $p<.05$.

Table 8. Regression Analyses of Final School Grades and SQTs on Principal Components for Marine Corps Specialties

		Principal Component Order of Entry											
MOS[a]	N	1	2	3	4	5	6	7	8	R_g	R_{g+s}	R_{diff}	SEE[b]
01T	1252	1	2	4	7					.411	.450	.039	5.335
031	3731	1	8	5	10	6				.411	.420	.009	7.461
033	688	1	8							.337	.362	.025	6.901
034	695	1	5	8						.251	.324	.073	7.110
035	727	1	9	10						.228	.292	.064	5.861
25U	864	1	6	10	9					.194	.274	.080	9.556

[a]MOS defined in Appendix A.
[b]SEE = Standard Error of Estimate.

There were some exceptions to the rule that the first PC composite always entered first. Therefore, the R_g column is a misnomer in some military occupations. An example is the Navy Rating 611T (Interior Communications Technician) job, in which PC number 8 entered first and the first PC entered second. There were also two Army MOSs (MOS 63D, Self-Propelled Field Artillery System Mechanic; MOS 63T, Bradley Fighting Vehicle System Mechanic) where PC composite number 2 entered first and the first PC entered second. Finally, for one Air Force specialty (AFSC 45450A, Aerospace Propulsion Specialist), PC number 7 was the only PC with any predictive utility. Ree and Earles (1990a) found that this AFSC had the lowest predictive utility for R_g of the 89 Air Force jobs investigated in that study.

With the exception the four jobs described above, the first PC or **g** was the best predictor of training success for 125 military jobs. These exceptions may reflect nothing other than sampling error. The remaining PCs entered the stepwise regression in the order of their contribution to explaining criterion variance.

Table 9 summarizes the results of this study, by Service, in terms of the order of entry of the estimates of specific abilities (PCs 2 through 10). Most noticeable in Table 9 is the fact that three of the Army jobs used eight of the PCs in the prediction equations. None of the other Services used that many. Only one Air Force and one Navy job used as many as six PCs in the prediction equations, and most Navy, Air Force and Marine Corps jobs had only three and four significant PCs in the prediction equations. These results may indicate differing criterion complexity across the Services and jobs.

The frequency with which specific PCs entered the prediction equations also differs across Services, with PC number 4 entering second more often in Navy equations, PC number 2 and number 3 entering second and third for Army and Air Force jobs, and no identifiable pattern for the small number of Marine Corps jobs (only six Marine Corps jobs met the sample size requirements). One interpretation of the frequency of the PCs entering the regression equations is that there are Service-specific patterns of criterion variance on the specific abilities involved.

Table 9. Frequency of Principal Components Occurrence in Regression Analysis

Principal component	Number of Times Entered on the Step Number: Step number 2	3	4	5	6	7	8	Total
				Army				
2	38	4	1	1	0	0	0	44
3	4	13	9	5	0	0	0	31
4	8	8	8	5	1	3	0	33
5	0	1	4	1	1	1	0	8
6	0	4	2	2	0	3	1	12
7	0	5	5	4	2	0	0	16
8	3	6	7	1	4	1	0	22
9	0	1	1	3	1	1	1	8
10	0	1	1	1	3	0	1	7
Total	53	43	38	23	12	9	3	181
				Navy				
2	5	3	3	0	0	0	0	11
3	1	4	1	0	0	0	0	6
4	9	3	1	0	0	0	0	13
5	0	1	1	0	0	0	0	2
6	1	0	2	2	0	0	0	5
7	1	0	1	1	0	0	0	3
8	0	2	0	1	0	0	0	3
9	0	0	0	0	1	0	0	1
10	2	2	1	1	0	0	0	6
Total	19	15	10	5	1	0	0	50
				Marine Corps				
2	1	0	0	0	0	0	0	1
3	0	0	0	0	0	0	0	0
4	0	1	0	0	0	0	0	1
5	1	1	0	0	0	0	0	2
6	1	0	0	1	0	0	0	2
7	0	0	1	0	0	0	0	1
8	2	1	0	0	0	0	0	3
9	1	0	1	0	0	0	0	2
10	0	2	1	0	0	0	0	3
Total	6	5	3	1	0	0	0	15
				Air Force				
2	12	3	0	0	0	0		15
3	5	4	2	1	1	0	0	13
4	6	7	4	2	0	0	0	19
5	1	1	1	0	0	0	0	3
6	6	2	1	1	0	0	0	10
7	5	4	2	0	0	0	0	11
8	1	1	0	1	0	0	0	3
9	2	2	1	1	0	0	0	6
10	0	2	1	0	0	0	0	3
Total	38	26	12	6	1	0	0	83

The results of this study replicated and extended the findings of Ree and Earles (1990a), that **g** is consistently the best predictor of the criterion of training success in military occupations. This finding was replicated for a number of Air Force occupational specialties and extended to those Navy and Marine Corps specialties investigated. Results from this study also suggest that **g** is a uniformly good predictor of the SQT criterion for a sample of 58 Army jobs examined. These results also indicate that there was significant variation among the Services in the pattern of prediction using specific abilities. The results of this research suggest that although **g** is extremely important for predicting military training success and SQT scores, it is not enough. For 118 of the 125 jobs investigated, measures of specific ability added to predictive utility. As Brogden (1946) noted, small increments in validity can have large practical value. The between-Service and between-job variation in the magnitude and pattern of the specific abilities' increment in predictive utility warrant the continued use of measures of specific abilities in military selection and classification.

The present investigation provides no clear suggestion as to how PC-weighted composites can be used to improve classification efficiency. A system such as the one suggested by Alley, Treat, and Black (1988) could be developed to cluster military occupations based on the similarity of principal component prediction equations. In effect, such a system would cluster individual occupations in terms of their unique regression of training success or first-term job performance criteria on g and **s**, and establish occupational clusters or classification systems on these clusters as Ree and Earles (1990a) have suggested.

Thorndike (1957) also proposed a system similar to the principal components approach used in this study. He used the term "principal composites" to describe a system which used decreasingly predictive, orthogonal components to make unique prediction composites using a training success criterion. However, as Ree and Earles (1990a) have suggested, Thorndike's system may be impractical in present military selection and classification systems, given the frequency with which the classification structure and the nature of military jobs change.

The Services now enjoy sophisticated, computerized initial job assignment and classification systems that make initial job assignments and choices based on algorithms that include ASVAB aptitude measures as well as other non-cognitive measures and job category information. Ree and Earles (1990c) reported that consideration of all these occupational facets (**g**, **s**, job classification, non-cognitive measures) of a job category provides almost half the predictive power of the full linear model used in their analysis.

information about specific jobs does improve prediction, as confirmed by the results of Ree and Earles (1990a, 1990c) and this study. There seems to be some situational specificity for these military jobs, but its overall effect in terms of predicted training criterion variance is relatively small.

Attempts to generalize the results of this research illustrate a problem in determining the relative contributions of general and specific abilities to prediction on a more theoretical level. The degree of situational specificity one finds, or the extent to which specific abilities result in practical and statistically significant increments to predictive validity, is limited by the measures. The present research provides evidence of how well the ASVAB measures general and specific cognitive abilities in predicting training success or SQT scores. In most instances, general ability was the most potent predictor, while specific abilities made a more modest, but useful contribution. These findings, however, do not necessarily generalize to other predictors or to other criteria. The contribution of general and specific components might differ if predictor batteries composed of other measures were used, especially batteries which include other facets such as vocational interests, biodata, or personality variables. Different findings might also accrue if job performance criteria were used. However, the current research contributed to the efficient selection and classification of military enlisted personnel by clarifying the role of specific and general cognitive abilities as measured by the ASVAB. It has been clearly demonstrated that the ASVAB is far more g saturated than its original developers envisioned, and that general ability is very predictive of the criteria used across a wide variety of military occupations.

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APPENDIX A: JOB TITLES WITH CRITERION MEANS AND STANDARD DEVIATIONS

Table A-1. Criterion Means and Standard Deviations for All Jobs Meeting Power Requirements

MOS	Name	N	Mean	SD
	Army			
11b	Infantryman	17,805	79.841	11.657
13b	Cannon crewmember	10,678	76.139	12.117
95b	Military police	9,066	78.620	7.881
64c	Motor transport operator	7,493	82.062	8.864
63b	Light wheel vehicle mechanic	6,948	63.148	10.062
71l	Administrative specialist	6,069	74.044	13.796
94b	Food service specialist	6,039	62.540	9.704
76y	Unit supply specialist	5,337	78.840	11.410
12b	Combat engineer	4,517	74.992	10.611
19e	M48/M60 Armor crewman	4,064	75.561	9.083
11c	Indirect fire infantryman	3,968	84.438	10.585
31c	Single channel radio operator	3,683	73.784	10.375
19d	Cavalry scout	3,319	69.520	10.687
31k	Combat signaler	3,129	64.476	9.508
76c	Equipment records and parts specialist	2,891	82.422	9.053
31m	Multi-channel communication system operator	2,834	77.559	10.530
11h	Heavy anti armor weapons infantryman	2,732	84.085	10.709
72e	Tactical telecommunications center operator	2,560	72.123	10.653
76v	Material storage & handling specialist	2,176	76.011	9.677
76w	Petroleum supply specialist	2,049	64.717	11.674
52d	Power generation equipment repairman	2,044	72.054	8.883
13f	Fire support specialist	1,899	75.926	10.986
36c	Wire systems installer	1,840	69.667	11.169
76p	Material control & accounting specialist	1,609	72.624	13.449
19k	M1 Armor crewman	1,497	76.068	10.339
63h	Track vehicle repairman	1,452	62.928	11.735
63t	Bradley fighting vehicle system mechanic	1,369	68.943	8.145
63w	Wheel vehicle repairer	1,367	57.221	10.183
75d	Personnel records specialist	1,342	66.225	13.128
16s	Manpads crew member	1,273	78.126	9.868
55b	Ammunition specialist	1,139	78.662	11.424
62b	Construction equipment repairer	1,095	74.563	12.641
12c	Bridge crew member	1,052	78.299	9.903
31v	Unit level communications maintenance	1,049	74.588	9.815

Table A-1. (Continued)

MOS	Name	N	Mean	SD
	Army			
15d	Lance crewmember	997	64.661	13.151
75b	Personnel administrative specialist	996	66.232	13.734
63n	M60A1/AS Tank system mechanic	984	61.195	8.409
62e	Heavy construction equipment operator	978	72.466	12.079
16p	Chapparral crew member	962	77.471	9.067
72g	Automatic data telecommunications center operator	959	73.140	9.681
67n	Utility helicopter repairer	951	71.018	9.243
73c	Finance specialist	761	63.300	10.219
82c	Field artillery surveyor	758	66.612	12.165
16r	Vulcan crewmember	738	76.764	7.768
67v	Observation/scout helicopter repairer	714	72.339	8.323
75c	Personnel management specialist	694	60.974	13.095
92b	Medical laboratory specialist	667	76.252	13.023
57h	Cargo specialist	639	60.842	12.888
05h	Electronic warfare/signal intelligence Morse intrepreter	637	87.812	8.346
63s	Heavy wheel vehicle mechanic	622	60.783	9.401
98c	Electronic warfare/signal intelligence	616	77.229	11.163
43e	Parachute rigger	613	81.630	13.394
63d	Self-propelled field artillery system mechanic	590	65.542	8.757
62j	General construction equipment operator	577	72.475	12.116
67y	Attack helicopter repairer	564	74.051	9.173
91e	Dental specialist	552	75.567	9.266
32d	Communications system, circuit controller	552	81.884	9.206
51b	Carpentry and masonry specialist	550	59.187	10.813

AFSC	Name	N	Mean	SD
	Air Force			
81130	Apprentice security specialist	8,830	78.163	19.159
81132	Apprentice law enforcement specialist	4,301	75.419	23.785
70230	Apprentice administrative specialist	3,922	88.429	14.091
45234	Apprentice tactical aircraft specialist	3,851	81.317	13.873
64530	Apprentice inventory management specialist	3,515	86.691	10.282
45730	Apprentice strategic aircraft specialist	2,712	81.282	14.039
90230	Apprentice surgical services specialist	2,378	77.248	21.885

Table A-1. (Continued)

AFSC	Name	N	Mean	SD
	Air Force			
45431	Apprentice aerospace ground equipment repairman	2,355	80.773	27.346
46130	Apprentice munitions system specialist	2,311	87.156	12.575
49131	Apprentice communications computer operator	2,204	84.569	14.129
45732	Apprentice airlift aircraft maintenance specialist	2,146	80.971	15.062
57130	Apprentice fire protection specialist	2,082	88.295	12.458
45430A	Apprentice aerospace propulsion specialist	2,003	79.259	25.688
73230	Apprentice personnel specialist	1,730	80.862	23.416
63130	Apprentice fuel specialist	1,692	86.437	14.753
30434	Apprentice ground radio communication specialist	1,513	76.200	33.263
27230	Apprentice air traffic control operator	1,269	63.049	38.683
60531	Apprentice air cargo specialist	1,075	84.297	13.682
42330	Apprentice aircraft electrical system specialist	995	79.039	29.569
90630	Apprentice medical administration specialist	945	83.377	15.768
46230F	Apprentice aircraft armament system specialist F-16	855	86.711	16.517
62330	Apprentice services specialist	831	85.915	13.417
98130	Apprentice dental specialist	821	81.432	23.735
42735	Apprentice airframe repair specialist	786	84.545	17.779
45434	Apprentice aircraft pneudraulic system specialist	781	79.246	25.255
32430	Apprentice precision measuring equipment specialist	770	75.948	31.838
32833	Apprentice precision measuring equipment specialist	675	64.271	42.009
32831	Apprentice precision measuring equipment specialist	646	73.223	35.580
46230E	Apprentice aircraft armament system specialist F-15	769	86.446	16.187
67232	Apprentice financial services specialist	742	80.182	19.201
32531	Avionics instrument system specialist	688	73.858	34.232
27630C	Apprentice aerospace control & warning system operator	681	84.135	12.761
45732C	Apprentice airlift aircraft maintenance C-9, T-43	645	23.834	38.478
32830	Apprentice avionics communications specialist	645	78.318	32.021

Table A-1. (Continued)

AFSC	Name	N	Mean	SD
	Air Force			
25130	Apprentice weather specialist	639	78.394	31.852
45433	Apprentice aircraft fuel system mechanic	627	82.241	23.687
45450A	Aerospace propulsion specialist	610	76.221	28.242
49231	Apprentice communication system radio operator	603	78.604	20.000
46230K	Apprentice aircraft armament system specialist B52	596	85.144	13.776
46330	Apprentice nuclear weapons specialist	592	81.745	26.501
55131	Apprentice construction equipment operator	578	88.820	11.216
81132A	Apprentice military working dog qualified	572	85.413	18.401
92430	Apprentice medical lab specialist	558	65.498	36.897
41131A	Apprentice missile maintenance specialist	552	86.491	15.289

RATING	Name	N	Mean	SD
	Navy			
6125	(MS) Mess management specialist	8,200	86.203	20.928
603v	(ET) Electronics technician	3,260	85.028	13.422
6001	(QM) Quartermaster	3,134	76.643	28.392
611e	(RM) Radioman	3,013	89.989	6.949
6005	(SM) Signalman	2,388	79.504	30.979
6515	(AE) Aviation electrician	2,365	72.304	31.086
604e	(ET) Electronics technician	2,122	88.863	11.659
6540	(OS) Operations specialist	2,076	76.058	30.425
6015	(STG) Sonar technician, general	1,910	86.002	15.575
607w	(GMG) Gunner's mate, gun	1,652	89.862	7.327
611t	(IC) Interior communications technician	1,519	78.190	18.106
6070	(EM) Electrician's mate	1,464	82.854	9.697
6301	(CTR) Cryptologic technician collection	1,222	71.439	37.808
60o8	(MR) Machinery repairman	1,189	75.275	24.599
6167	(DP) Data processing technician	1,108	89.737	19.318
6278	(AC) Air traffic controlman	986	54.211	39.915
6172	(STS) Sonar technician submarine	977	85.727	10.559
6302	(CTT) Technician non-Morse	965	90.279	20.687
6537	(AW) Aviation anti-submarine warfare operator	908	71.447	34.446
6477	(SH) Ship's serviceman	709	89.023	7.974
601e	(CTO) Cryptologic technical communication	692	93.750	10.733
6472	(AG) Aereographer's mate	627	74.802	32.118

Table A-1. (Concluded)

MOS	Name	N	Mean	SD
	Marine Corps			
0311	Rifleman	3,731	83.940	8.209
0151	Administrative clerk	1,252	93.070	5.950
2531	Field radio operator	864	87.910	9.877
0351	Assaultman	727	85.761	6.086
0341	Mortarman	695	85.022	7.462
0331	Machine gunner	688	83.833	7.347

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